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Predicting water resistance and pitching angle during take-off: an artificial neural network approach

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ABSTRACT

This research addresses the challenges faced by seaplanes and amphibious aircraft during takeoff and landing on water, emphasizing the limitations and costs associated with traditional towing tank tests and computational fluid dynamics (CFD) simulations. The study proposes an innovative approach that employs artificial neural networks (ANN) to predict water resistance and pitching angle during amphibious aircraft take-off, minimizing the reliance on expensive towing tank tests. The ANN models are developed and optimized using Bayesian optimization, showcasing improved accuracy in predicting water resistance and pitching angle. The research demonstrates the potential of machine learning, specifically ANNs, to significantly reduce the need for costly experimental tests, providing an efficient alternative for designing amphibious aircraft. The results indicate high accuracy in predicting water resistance and pitching angle, offering substantial time and resource savings during the experimental phase. However, the study highlights the need for model adaptation for different designs and test variations to enhance overall applicability.

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1. INTRODUCTION

Seaplanes and amphibious aircraft face unique challenges during takeoff and landing on water primarily due to water resistance, which significantly impacts their performance. Accurately assessing behavior during crucial phases is essential for safety and compliance with aviation regulations. Two main methods are used to gather data on seaplane performance in water: towing tank tests involve using a scaled model of the seaplane towed through a water tank to analyze hydrodynamic behavior [1], while computational fluid dynamics (CFD) simulations numerically model the air-water flow field around the seaplane, offering insights into its hydrodynamic performance [2]–[5]. However, both methods are costly, with towing tank tests limited by tank size and CFD simulations requiring significant computational resources. Leveraging machine learning, specifically artificial neural networks (ANN), for data prediction based on statistical analysis could potentially mitigate these challenges and reduce costs in seaplane performance assessment.

Driven by their unique blend of intelligent control and brain-inspired functionality, ANN has shown promising results in diverse areas of engineering applications. The ANN algorithm has been used to conduct data prediction and design optimization. Several researchers explore ANN programming to train experimental data about Savonius rotors [6], to accurately predict turbulence in fluid flows [7], [8], and hydrodynamic

performance of bionic fish in self-propelled motion [9]. Gul *et al.* [10] used ANN and grey-Taguchi method to optimize the performance and emissions of a diesel engine fueled with biodiesel blends. Both the experimental and ANN-simulated results validate the effectiveness of achieving improvements [10].

In the context of naval applications, ANNs can learn intricate patterns from towing tank test data or CFD simulation results [11]. Their rapid predictive capabilities extend to estimating total resistance, proving particularly useful in the early stages of designing preliminary configurations, such as the trimaran-small waterplane area centre hull (Tri-SWACH) [12]. Shehata and Dashtimanesh [13] suggests that machine learning, particularly recurrent neural networks (RNNs) with gated recurrent unit (GRU) architecture, can be a valuable tool for designing high-speed crafts with improved seakeeping performance. Radojčić *et al.* [14] employed conventional regression analysis methods and ANN to develop mathematical models for the resistance, trim, and wetted length of the experimental model basin series 50. Najafi *et al.* [15] using ANN to evaluate initially and experimentally via model-test the hydrodynamic performance of three different hydrofoils for a catamaran hull. Cepowski [16] evaluated the effectiveness of an ANN model for predicting the added wave resistance coefficient of ships in regular head waves. Predictions showed good correlation with measured data, with most discrepancies falling within a range of -1.2 to 1.2 [16].

For seaplane design, water resistance is a crucial parameter in determining aircraft performance when moving on the water surface. Atmaja *et al*. determine the water drag of various floater lengths and the distances between the two floaters. The ANN model has been proven to accurately predict the water resistance of the floater, approaching the value obtained from calculations using the Savitsky method, where the correlation coefficient (R-squared) between the two is close to 1, and the error (root mean square error (RMSE)) value is close to 0 [17]. They successfully predicted the aerodynamic coefficients of an amphibious aircraft using grid search cross validation based on wind tunnel test data [18]. Du *et al.* [19] developed two models (ANN and nonlinear polynomial fitting) to predict resistance based on principal components. They use a surrogate model to analyze how sensitive resistance is to initial parameters such as trim angle, waterplane area, and specific dimensions [19].

Building on the predictive capabilities of ANN models in predicting water resistance for seaplanes, this study aims to enhance their predictive capabilities by utilizing experimental data from hydrodynamic testing laboratories. By leveraging this dataset, the research aims not only to forecast water resistance but also to predict the pitching angle of twin-float amphibious aircraft during takeoff. The main objective is to streamline the design evaluation process by reducing reliance on costly towing tank tests through the development of optimized ANN models. These models are refined using Bayesian optimization techniques to fine-tune their hyperparameters for improved accuracy and efficiency.

2. METHOD

As previously described, one method utilized to assess the hydrodynamic performance of seaplanes involves conducting towing tank tests using scaled models. In these tests, various parameters are meticulously recorded to evaluate seaplane performance. These parameters encompass the test ID, which serves as a unique identifier for each conducted test. Additionally, the center of gravity position (CG in % of mean aerodynamic chord), model load (kg), acceleration (m/s^2), velocity (m/s), water resistance (Fxw in N), and pitch angle (degree) are measured and documented during the experiments. It is worth noting that the towing tank test employs the same design and Froude number as depicted in Figure 1.

Figure 1. Towing tank test of an amphibious aircraft

The parameters targeted for prediction using ANN are water resistance and pitching angle, with input parameters including CG position, model load (weight), acceleration, and velocity. The dataset used to construct ANN models is divided into training and testing datasets, allocated based on towing test results that reflect diverse physical characteristics. The division of training and test data is determined by the data ID numbers assigned during the towing tank experiment. Specifically, the training data comprises all test data IDs

except for IDs 2118 and 2119, which are reserved for testing purposes. The training dataset constitutes 78% of the total data, while the testing dataset comprises the remaining 22%. The development flowchart of the ANNs model is depicted in Figure 2.

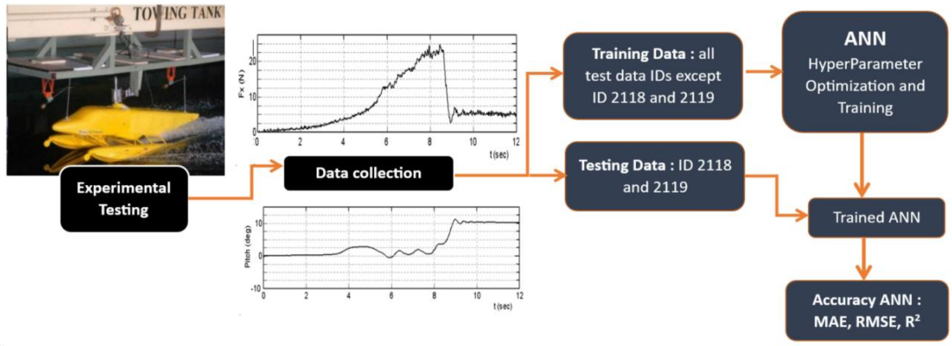


Figure 2. Flowchart of the development of ANNs model

To ensure uniformity in the dataset, data normalization is performed on both the training and test data. Data normalization is a widely employed technique in data mining and is used to standardize values within a dataset to a common scale. This is crucial because many machine learning algorithms are sensitive to variations in input feature scales, and normalizing the data can enhance algorithm performance. Furthermore, data normalization facilitates more effective model learning by equalizing the data's scale. In this research, the min-max method is employed for data normalization, with the formula for this method detailed in (1). This technique involves transforming each data entry ($\acute{x}$) based on the original value (x), the minimum ($min(x)$), and maximum ($max(x)$) values of the data attribute. The resulting normalized values fall within a specified range defined by $new_{min}(x)$ and $new_{max}(x)$. By equalizing the scale of the data, this normalization approach is instrumental in improving the performance of machine learning algorithms, particularly by mitigating sensitivity to variations in input feature scales.

$$X_{norm} = \left[\frac{\acute{x} - min(x)}{max(x) - min(x)} \times \left(new_{max}(x) - new_{min}(x)\right)\right] + new_{min}(x) \tag{1}$$

ANNs are powerful tools for predicting complex relationships between input and output data, making them well-suited for tasks like predicting water resistance and pitching angle in seaplanes. However, achieving optimal performance with ANNs requires selecting appropriate hyperparameters, such as the learning rate, iteration count, and layer architecture, which significantly influence the model's behavior during training and testing. Inadequate hyperparameters can lead to overlooked patterns or suboptimal performance. Therefore, in this study, we propose using Bayesian optimization to fine-tune the hyperparameters of ANNs specifically tailored for predicting the behavior of twin-float amphibious aircraft in terms of water resistance and pitching angle.

Bayesian optimization, a widely used method in machine learning, offers an efficient approach to obtaining optimized hyperparameter values, thereby improving model performance while saving time. Several studies have demonstrated the effectiveness of Bayesian optimization in various machine learning models and domains [20]–[24]. By leveraging automatic search algorithms, Bayesian optimization can efficiently explore the hyperparameter space and identify optimal combinations, enhancing efficiency and accuracy. Additionally, Bayesian optimization is resistant to biases present in training data and can provide more accurate estimates of optimal hyperparameter combinations. The hyperparameters to be optimized for our ANN models are listed in Table 1. There are some ANN hyperparameters that do not need to be optimized. These hyperparameters include an EPOCH set at 100, a batch size of 10, and the optimizer as Adam. This systematic approach aims to enhance the overall performance of the ANN model through meticulous hyperparameter tuning.

Table 1. ANN hyperparameters to be optimized

Hyper-parameter ANN	Range optimization
Learning rate	1e−3 up to 1e−2
Number of neurons	4 up to16
Number of hidden layers	1 up to 5
DropOut value	0 up to 5

Activation function	Elu, Relu, TanH, Sigmoid

To evaluate the performance of predictive models, mean absolute error (MAE), RMSE, and R-squared (R^2) are used. MAE is a measure of the average absolute errors between the predicted values (y_i) and the actual values ($\hat{y}_i$). It is determined by computing the mean of the absolute variances between the predicted and actual values, as illustrated in (2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

RMSE stands for the square root of the mean squared differences between predicted and actual values. Unlike MAE, RMSE places greater emphasis on significant errors by squaring the differences before averaging and subsequently taking the square root, as depicted in (3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

R^2 serves as a statistical metric indicating the extent to which the independent variables in a model account for the variance in the dependent variable. With values ranging from 0 to 1, a score of 0 implies the model fails to explain any variability, while a score of 1 signifies a complete explanation of all variability. R^2 is more informative and accurate than MAE and RMSE [25]. The formula for calculating R^2 is presented in (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y_i}\right)^2} \quad (4)$$

3. RESULTS AND DISCUSSION

In this study, we present the optimal hyperparameters identified through Bayesian optimization for predicting water resistance and pitch angle in ANN models. These hyperparameters were meticulously tuned through a tailored optimization process, including the number of hidden layers, neurons in each layer, activation functions, dropout values, and learning rate. The optimal hyperparameters for predicting the output Fxw in the ANN model are as follows: 4 hidden layers with 14, 4, 4, and 4 neurons in each layer, utilizing the activation functions rectified linear unit (ReLu), exponential linear unit (Elu), Elu, and Elu, respectively. The dropout values for each layer are 0.085269, 0, 0, and 0, and the learning rate is set at 0.00231. These hyperparameter configurations have been determined through a Bayesian optimization process specifically designed to enhance the accuracy and effectiveness of the ANN model in predicting the output Fxw (water resistance). The architecture of the ANN is visually represented in Figure 3.

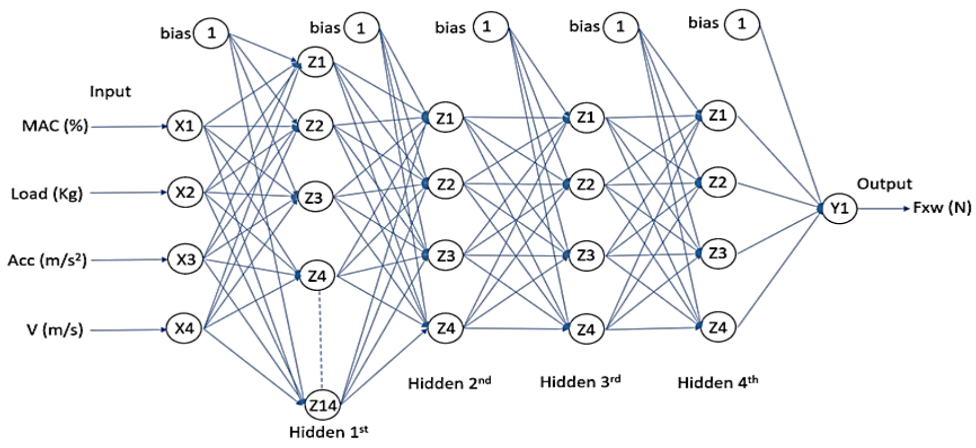


Figure 3. Optimal ANN architecture for output water resistance

The optimal hyperparameters for predicting the output pitch (deg) in the ANN model are specified as follows: a four-layer architecture with 10, 4, 4, and 4 neurons in each hidden layer, utilizing the activation functions ReLu, Elu, Elu, and Elu, respectively. Dropout values for each layer are set at 0.098582, 0, 0, and 0,

and the learning rate is established at 0.00615. These hyperparameter configurations have been determined through an optimization process, specifically designed to enhance the accuracy and effectiveness of the ANN model in predicting the output pitch. The architecture of the ANN is visually presented in Figure 4.

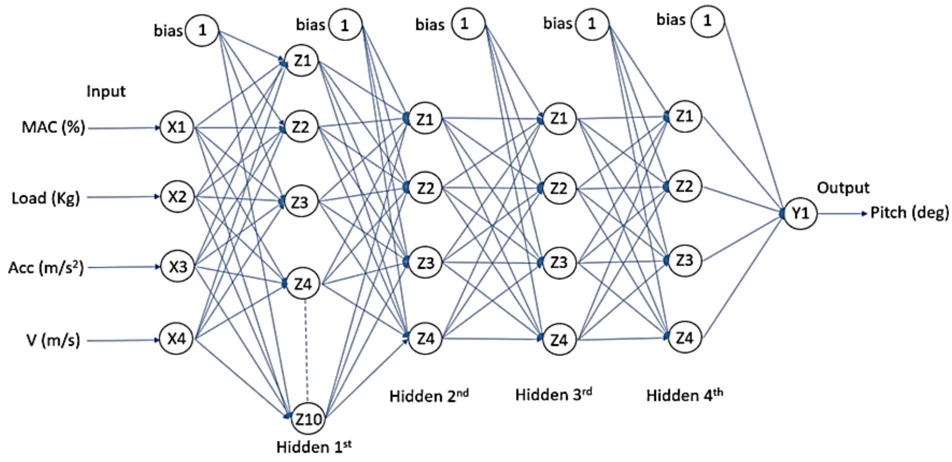
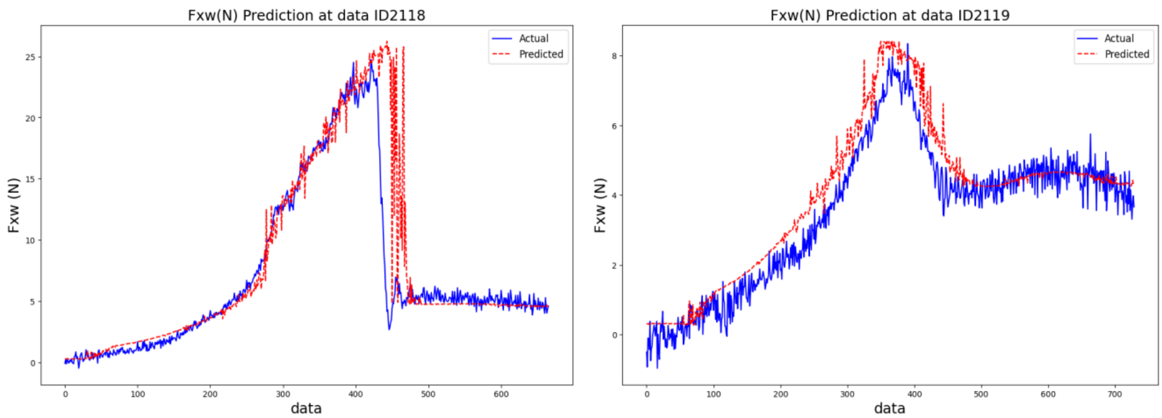


Figure 4. Optimal ANN architecture for output pitch (deg)

3.1. Results of water resistance prediction

Two distinct sets of characteristics were utilized in the testing phase to assess the performance of the constructed ANN models. The significance of dataset ID numbers 2118 and 2119 is underscored by their unique physical attributes derived from towing test results, as shown in Figure 5. Figure 5(a) illustrates the actual and predicted data for ID numbers 2118, while Figure 5(b) shows the same for ID numbers 2119. The ANN models effectively predict patterns specific to each ID, as depicted in the chart illustrating the predicted data alongside the actual towing tank data for water resistance. Remarkably, despite the differing physical characteristics of ID numbers 2118 and 2119, the ANN successfully captures and predicts similar patterns observed in the actual towing tank data for both IDs.



(a) (b)

Figure 5. Predicted and actual water resistance of dataset (a) ID 2118 and (b) ID 2119

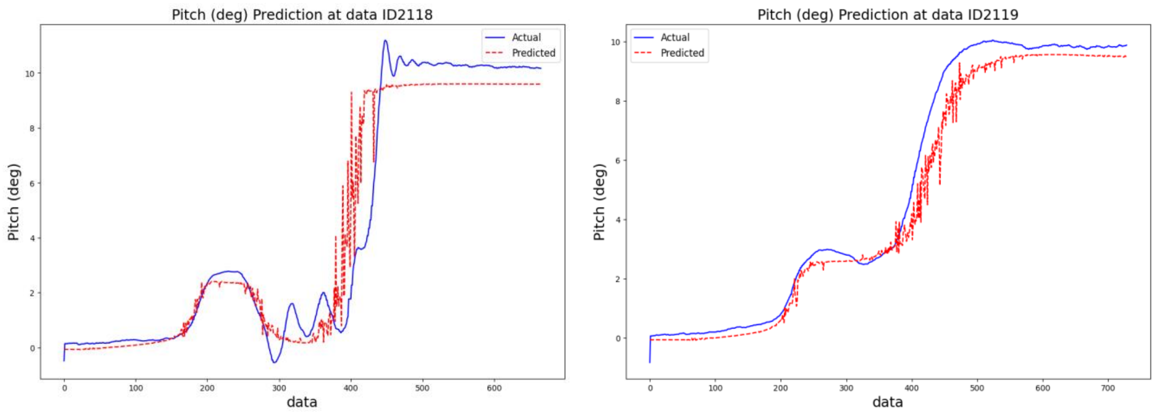
The evaluation of ANN models for predicting water resistance involved assessing key metrics, including MAE, RMSE, and R^2. The results, detailed in Table 2 for both training and testing data for IDs 2118 and 2119, reveal notable scores. These results indicate high accuracy, as both MAE and RMSE scores are close to zero, and R^2 scores are close to one for both IDs.

Table 2. MAE, RMSE, and R² score of data training and testing of water resistance

Dataset	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
Training Data	0.01023	0.01982	0.98199	-	-	-
Testing Data ID 2118	-	-	-	0.02661	0.07521	0.69735
Testing Data ID 2119	-	-	-	0.01187	0.01489	0.87769

3.2. Results of pitching angle prediction

The results of the pitching angle prediction are showcased in Figure 6, with Figure 6(a) representing ID number 2118 and Figure 6(b) illustrating ID number 2119. The charts vividly demonstrate that the predicted data aligns closely with the pattern observed in the towing tank test results for both IDs, confirming the model's ability to accurately predict pitch behavior. This alignment highlights the ANN model's capability to capture dynamic changes in pitching angles, even with varying physical attributes between the two datasets. Notably, the model effectively adapts to the different conditions of ID 2118 and ID 2119, further validating its robustness in handling complex, real-world testing scenarios.



(a) (b)

Figure 6. Predicted and actual pitch angle of a dataset (a) ID2118 and (b) ID2119

Table 3 presents the MAE, RMSE, and R² scores for pitch angle in both training and testing data for IDs 2118 and 2119. The MAE and RMSE values are close to zero, and the R² scores approach one, indicating high accuracy in the prediction of pitch angle. These results reflect the ANN model's strong ability to generalize across different datasets with minimal error. Moreover, the higher R² scores in testing data suggest the model effectively captures the variance in pitch angle across diverse towing test conditions.

Table 3. MAE, RMSE, and R² score of data training and testing of pitch angle

Dataset	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
Training Data	0.02016	0.03177	0.98764	-	-	-
Testing Data ID 2118	-	-	-	0.05232	0.08822	0.92494
Testing Data ID 2119	-	-	-	0.03306	0.04703	0.97531

3.3. Discussion

Recent studies have explored various methods for predicting water resistance and pitch angle, crucial parameters in seaplane design and performance analysis. One approach involves CFD, employing reynolds-averaged navier-stokes (RANS) equations with the volume of fluid (VOF) method. Guo *et al.* [3] utilized CFD to predict the resistance and attitude of a seaplane during takeoff, reporting errors of 6.5% for trim and 8.2% to 13.9% for resistance. Additionally, ANN has demonstrated promising results in predicting water resistance and pitch angle across various applications, as depicted in Table 4, with high accuracy reported in [12], [14]–[16].

In comparison, our ANN models demonstrate enhanced accuracy and effectiveness in predicting both water resistance and pitch angle, with water resistance errors (MAE) ranging from 0.01187 to 0.02661, RMSE

ranging from 0.01489 to 0.07521, and R^2 ranging from 0.69735 to 0.87769. For pitch angle errors (MAE), the range is from 0.03306 to 0.05232, with RMSE ranging from 0.04703 to 0.08822, and R^2 squared ranging from 0.92494 to 0.97531. These results highlight the efficiency of predicting water resistance and pitching angle through ANN modeling and underscore the potential for significant time and resource savings in the experimental phase. However, it is essential to note that the current ANN models are designed for a specific twin-float design and Froude number, requiring the reconstruction of models for different twin-float designs based on specific towing tank tests. This adaptation involves expanding the dataset to include float design parameters as inputs. Additionally, accounting for variations in test procedures can further improve the models' accuracy and applicability. Looking forward, the exciting prospect of developing virtual towing tanks using machine learning technologies holds promise for advancing the efficiency and effectiveness of amphibious aircraft design processes.

Table 4. Recent research for predicting water resistance and pitch angle

Reference	Method	Application	Error
Guo *et al.* [3]	CFD (using RANS equations with VOF method)	Predict the resistance and attitude of a seaplane taking off	Trim: 6.5% Resistance 8.2% - 13.9%
Carter *et al.* [12]	ANN	Resistance prediction for preliminary tri-swach design	MAE: 10%
Radojčić *et al.* [14]	Regression analysis and ANN	The resistance and trim of series 50 experiments with V-bottom motor boats	R^2: 0.9719 - 0.9834 RMSD: 0.3185 - 0.4136 RMS: 7.00% - 9.66%
Najafi *et al.* [15]	ANN	Hydrofoil- supported catamarans	Resistance: MSE: 0.000683; R^2: 0.99438 Trim: MSE: 0.00688; R^2:0.92918
Cepowski [16]	ANN: multilayer perceptron (MLP), general regression neural network (GRNN), radial basis function (RBF)	Prediction of the ship added resistance	MSE: 1.1 - 1.87

4. CONCLUSION

In conclusion, this study demonstrates the efficacy of ANN in predicting water resistance and pitching angle for twin-float amphibious aircraft during takeoff. By leveraging experimental data from hydrodynamic testing laboratories and employing Bayesian optimization techniques for hyperparameter tuning, the ANN models achieve high accuracy and efficiency in predicting these crucial parameters. The results highlight the potential of ANN modeling to streamline the design evaluation process and reduce reliance on costly towing tank tests. However, further research is needed to adapt the models for different twin-float designs and towing tank test procedures, as well as to explore the development of virtual towing tanks using machine learning technologies. Overall, ANN modeling shows promise for advancing the efficiency and effectiveness of amphibious aircraft design processes.

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